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The indirect carbon emission from household consumption in China between 1995–2009 and 2010–2030: A decomposition and prediction analysis

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ABSTRACT

Indirect carbon emissions from households can be redefined and recalculated using an input-output model. This paper combines multivariate regression analysis with input-output technology and a structural decomposition analysis to examine their impact and predict carbon emissions in the future. The results show that urban employment, rapid urbanization, and the two-child policy are the main reasons for the population variable having a magnifying effect on increasing indirect carbon emissions. Growing household incomes and improved living standards will pose a serious threat to responses to climate change in most developing countries. The growth rate of indirect carbon emissions from household consumption will slow under the two-child policy, after adjusting for other determinants such as consumption composition and technical progress in energy-intensive sectors. The steady and continuous increase of indirect emissions is mainly trouble lies the stable consumption of secondary industry products and the rapid growth in consumption of tertiary industry products. This paper also presents several policy implications for the government and other decision-making organizations.

1. Introduction

With the rapid pace of industrialization and urbanization around the world, climate change has become society's most significant environmental and economic challenge. In China, sustainable development has been a strategic goal of the country since 1996 in its economic and social development. However, China has been searching for the most beneficial resolution to its dilemma of whether its responsibility is to maintain domestic economic growth, with the goals of reducing poverty and increasing the standard of living of the Chinese population, or to control the rapid increase of greenhouse gas (GHG) emissions. Therefore, the Chinese government signed the 2015 Paris Agreement, committing to reach a maximum total carbon emission peak by 2030 and thus entering a stage of absolute reduction in total emissions.

From the perspective of household consumption, the driving forces of domestic economic growth are expanding household consumption and upgrading consumption composition, such as the proportion of residents' entertainment means and medical care. The Chinese government has long been aware of the vital role of household consumption in low carbon emissions and has been actively advising households to consume products with a low carbon footprint (Qu, Maraseni, & Liu, 2015). In 2015, the Chinese government proposed the full implementation of its two-child policy to buffer the economic and social effects of its aging population. The United Nations raised its worldwide population estimate from 9 billion to 9.7 billion by 2050 before the two-child policy decision was made. This means that China will face greater pressure to reduce its GHG emissions while maintaining economic growth. Population growth and rapid urbanization not only cause increasing demands for overall household consumption but also add to the mounting effects of production and indirect carbon emissions (see Table 1).

Because of a rapid change in consumption composition, such as a priority in transportation and housing instead of food and clothing, the potential growth of China's per capita household consumption is relatively higher than that of other developed countries. China's total household consumption expenditure per capita in 2014 was US$1420 (price in 2005), whereas those in the US, Japan, and Korea were US $31469, US$22,149, and US$11,783, respectively. Furthermore,

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Table 1
Overview of studies about the carbon emissions from household consumption.

Author	Period/Reference year	Description	Method	Conclusion
Jones and Kammen (2011)	2005	Quantify the carbon footprints of typical U.S. households in 28 cities for 6 household sizes and 12 income brackets to assess household and communities climate impacts	Consumption-based LCA	The carbon footprint of the average U.S. household, totaling 48 t CO_2 per year, or roughly 20 t CO_2 per person, for the baseline year of 2005
Matsuda et al. (2012)	2008	Analysis of household waste management scenarios for Kyoto with a special emphasis on food waste reduction activities is conducted	LCA	The prevention of food losses enhanced by separate collection led to a significant reduction in GHG emissions
Yano et al. (2014)	2008–2010	Quantify the life-cycle greenhouse gas (GHG) emissions reduction that could be achieved by 2 replacements	LCA	Replacement of fossil-derived materials with biomass-based materials could reduce life-cycle GHG emissions by 14–20%. Source separation and recycling should be promoted
Saner et al. (2013)	2010	Using a small village in Switzerland to assess the environmental impacts of all individual households and to characterize different household consumption patterns	LCA	21% of the households in the investigated region were responsible for 50% of the total greenhouse gas emissions
Liu et al. (2011)	1992–2007	The impact of China's increased urban and rural household consumption on carbon emissions	IOA	The direct and indirect CO_2 emission from household consumption accounted for more than 40% of total carbon emissions from primary energy utilization in 1999–2007
Zhu et al. (2012)	1992–2005	Investigating the indirect carbon emissions and its impact factor from residential consumption in China for 14 sectors	IOA	Restructuring the economy and improving efficiency, rather than for lowering the consumption scale, should be adopted by China to achieve the targets of energy conservation and emission reduction
Das & Paul, 2014	1993/1998/2003/2006	Describing direct and indirect CO_2 emissions by households for 115 sectors in India	IOA	Activity, structure and population effects are the main causes of the CO_2 emission increase from household fuel consumption
Steen-Olsen et al. (2016)	1999–2012	Assessing the carbon footprint of Norwegian household consumption for 12 sectors	IOA	Household energy use is largely based on hydropower and hence contributes comparatively little to the overall expenditure elasticity of household carbon footprint
Seriño and Klasen (2015)	2000/2006	Estimation of household carbon emission from the consumption of 240 sectors in the Philippines	IOA	Unless consumption patterns change, emissions will be further increases as households become more affluent
Zhang et al. (2015)	2000–2010	Examining the indirect energy consumption and CO_2 emission caused by household consumption for 28 sectors in China	IOA	The indirect energy consumption and CO_2 emission appear the main parts of total energy consumption and CO_2 emission caused by household consumption, accounting for 69–77% and 77–84%, respectively
Yuan et al. (2015)	2002/2007	Calculating China's indirect carbon emissions from residential consumption and investigate the regional variations' impact for 8 sectors	IOA	Expansion of urbanization and upgrade of consumption structure play important roles in the growth of residential indirect emissions
Perobelli et al. (2015)	2003/2009	Impact of Brazilian household consumption on the CO_2 emissions in 8 household group of 15 sectors	IOA	Trade-off exists between the greater satisfaction that the household groups find in consumption and the increasing setbacks in emissions from the restructuring and modification of the consumption basket
Ferguson and MacLean (2011)	1997	Estimating direct burdens and indirect burdens for US and Canada household for 30 expenditure and two activity categories	IO-LCA	Compared with Canada, per capita US household expenditures were 70% higher, while per capita household energy use and GHG emissions were only 10% and 44% higher, respectively
Onat et al. (2014)	2002	Emissions through the construction, use, and disposal phases were calculated for 3 scopes and 12 activities	IO-LCA	Use phase emissions are found to be the highest with 91% of the total emissions through all of the life cycle phases of the U.S. buildings
Miehe et al. (2016)	2004	Calculating regionalized household carbon footprint in Germany for 16 sub-national regions, 15 different household sizes, and 8 different income and age categories	IO-LCA	Indirect emissions from consumption as the largest share of household carbon footprints, although this is subject to fluctuation based on household type

China's household consumption only accounts for 37.4% of the country's GDP, and the corresponding percentages for the US, Japan, and Korea are 68.4%, 60.7%, and 50.3%, respectively. Especially in the context of rapid urbanization, Chinese national policies are focused on expanding domestic demand and boosting consumption. Increasing household consumption and development will have a significant impact on China's carbon emissions (Dai, Masui, Matsuoka, & Fujimori, 2012). Therefore, studying carbon emissions from the perspective of household consumption is required to achieve the current emission reduction goals and support the long-term development of China's low carbon economy.

Previous studies have explored energy consumption in the residential sector by examining different countries and using different perspectives. However, none of these studies used a combination of structural decomposition analysis (SDA) and regression analysis method, nor did any of them provide a comprehensive picture of carbon emissions from the perspective of household consumption, which can be attributed to these studies' narrow review. Given this background, the current study aims to answer the following questions: (1) Has China's household consumption reached the stage of low carbon development? (2) How do determinant factors influence the Chinese population's carbon emissions produced via consumption? Because of the uncertainty of long-term reduction targets in the Paris Agreement and Chinese population policy, the trend of carbon emissions from household consumption is also uncertain. Therefore, this study includes a prediction section concerning low carbon development to answer the last question: (3) What is the trend of indicate carbon emissions produced via household consumption in the future?

Our article starts with the theoretical framework of indirect emissions. Section 2 discusses the framework of indirect carbon emissions from household consumption (hereafter called ICEH). Section 3 describes the methodologies and models. Section 4 introduces the data resource and the evolution of ICEH in China and the determinant factors of carbon emissions from household consumption, as well as predictions concerning the future development of indirect household carbon emissions. Section 5 presents the conclusions and policy suggestions.

2. The theoretical framework of indirect carbon emissions from household consumption

Based on the definition of carbon emissions by Wiedmann and Minx (2008), those from household consumption have two main types: direct and indirect (Zhou & Wang, 2011; Zhang, Luo, & Skitmore, 2015; Qu et al., 2015). Generally, there are two major methodologies for calculating indirect carbon emissions from household consumption; one is a bottom-up approach called life cycle assessment (LCA), which can assess the carbon emission performance of residential activities. For example, plastic materials (Yano, Hirai, Sakai, & Tsubota, 2014), home composts (Quirós et al., 2014), biogas digesters (Vu, Vu, Jensen, Sommer, & Bruun, 2015), household waste management and food waste reduction activities (Matsuda, Yano, Hirai, & Sakai, 2012), fresh food e-commerce business (Guo, Wang, Fan, & Gen, 2017), and GHG emissions from consumer expenditures (Jones & Kammen, 2011; Saner, Heeren, Jäggi, Waraich, & Hellweg, 2013), among others, can be calculated. However, the LCA approach does not apply to any macro-level analysis because it is data and time intensive.

Another method is input–output analysis (IOA), which provides an alternative top-down approach to measuring carbon emissions from household consumption using scale, structure, and other macro dimensions. Basing on the input–output table, we can determine the relationship among sectors of the national economy with a Leontief inverse matrix (Leontief, 1970). Many studies have proved that IOA is superior in calculating the amount of residential carbon emissions at the macroeconomic (Wiedmann & Minx, 2008; Hertiwich, 2011; Donato, Lomas, & Carpintero, 2015) and regional levels, as shown in studies conducted in Australia (Lenzen, 1998), Brazil (Perobelli, Faria1, & Vale1, 2015), the Philippines (Seriño & Klasen, 2015), India (Das & Paul, 2014), Norway (Steen-Olsen, Wood, & Hertwich, 2016), Denmark (Munksgaard, Pedersena, & Wien, 2000), and China (Liu, Wu, Wang, & Wei, 2011; Zhou & Wang, 2011; Cui, Peng, & Zhu, 2015; Song & Cui, 2016; Zhang, Bian, Tan, & Song, 2017; Cui & Song, 2017). These researchers confirmed that ICEH play a key role in total carbon emissions. Total household consumption, energy intensity (Zhu, Peng, & Wu, 2012), and urbanization rate (Li, Zhao, Liu, & Zhao, 2015; Yuan, Ren, & Chen, 2015) are also key determinants for indirect emissions from household consumption.

Recently, hybrid methods have been developed to measure indirect household emissions, and these methods can complement one another's advantages and strengths; one example is combining regression with LCA (Gardezi, Shafiq, Zawawi, Khamidi, & Farhan, 2016) or IOA (Ala-Mantila, Heinonen, & Junnila, 2014). Moreover, the IO–LCA method can calculate not only detailed information on a particular product but also the aggregate results for macroeconomic purposes; it was used by Feng, Zou, and Wei (2011) and Fan, Guo, Marinova, Wu, and Zhao (2012) in China, by Ferguson and MacLean (2011) and Onat, Kucukvar, and Tatari (2014) in the US, and by Miehe, Scheumann, Jones, Kammen, and Finkbeiner (2016) in Germany. Other methods include the customer life cycle approach (Bin & Dowlatabadi, 2005; Wang & Yang, 2014), the emission coefficient method (Kadian, Dahiya, & Garg, 2007; Liu, Spaargaren, Heerink, Mol, & Wang, 2013; Salehi et al., 2017), the Working–Lesser model, and multilevel structural equation modeling analysis (Geng et al., 2017).

We found that many factors identified by previous research are significant determinants of carbon emissions, such as number of households or average size of households; these demographic variables (i.e., household dynamics) influence related environmental outcomes at the national level. Based on the stochastic impacts by regression on population, affluence and technology (STIRPAT) model, which is utilized to study the drivers of carbon emissions (Liddle, 2015; Shuai, Shen, Jiao, Wu, & Tan, 2017; Wang et al., 2017). Knight and Rosa (2012) found that the number of households is a better predictor of total fuelwood consumption than the average household size. Li, Lu, Ding, and Zhang (2017) proposed an embed STIRPAT CGE model to improve accuracy and rationality while quantifying carbon emissions drivers. However, many determinant effects are distinguished in the SDA and STIRPAT decompositions (Ding, Qu, & Niu, 2016; Guan, Kang, & Shao, 2017). The SDA approach uses a greater amount of data and a more complex economic model, allowing for a more detailed analysis of technological and final demand effects. The STIRPAT method is used to identify the primary drivers of environmental harm and explore the interactions among four components: population, affluence, environment, and technology.

In summary, there are two uncertainties in calculating and predicting indirect and total carbon emissions from household consumption. First, there is not many literatures about accurate definition of indirect and total carbon emissions from household consumption (Zhang, Caron, & Winchester, 2018). In this study, we define residential direct carbon emissions as carbon emissions from burning fossil fuels in residential energy consumption (such as heating and transportation). ICEH refer to carbon emissions from burning fossil fuels for producing non-energy products and services for residential consumption. For example, consuming food does not cause carbon emissions directly, but electricity, coal, and other energy sources are used indirectly to produce food that is consumed by households. Second, there is a double-counting problem when calculating indirect carbon emissions, which means that carbon emissions from the household consumption of energy products have been accounted for in direct carbon emissions from household consumption. The physical quantity of energy and value quantity of energy sectors describe the same thing. Therefore, we should treat carbon emissions from the household consumption of non-energy products and services as a part of residential indirect carbon

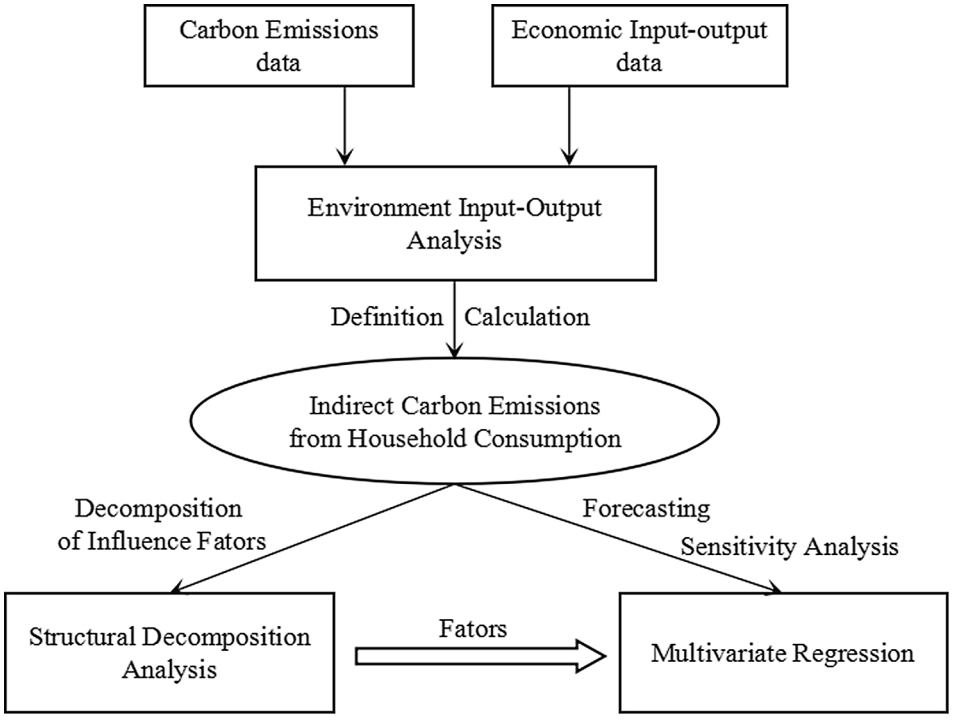

Fig. 1. The research framework of indirect emissions from household.

emissions; otherwise, direct carbon emissions from residential energy consumption will be counted twice. In this paper, we define direct carbon emissions from household consumption as equaling burned fossil fuels in residential energy consumption, multiplied by a carbon emissions factor. ICEH equal the total emissions requirement coefficient, multiplied by the residential consumption of non-energy products and services. Therefore, the total residential carbon emissions equal the sum of the direct and indirect carbon emissions from household consumption.

Choosing a model obviously often depends on a study's motivation and data availability. In this paper, the input–output tables provided by the World Input–Output Database (WIOD) and the available carbon emission data in satellite accounts are used to measure and describe the trend of carbon emissions from household consumption in China. Meanwhile, we use an SDA approach to explore the determinant factors of indirect carbon emissions, which can provide targeted and effective suggestions for future emission reduction policies (the framework of this study, see Fig. 1). Despite the high number of studies on carbon emissions (or carbon footprint) from household consumption, our work differs in terms of the following innovative points: First, it clarifies the definition and accounting method of indirect carbon emissions from household consumption. Second, a non-competitive input–output table is used in this study to distinguish the difference between domestic and imported goods. Existing studies have mainly used a competitive input–output table that considers domestic and imported goods as homogenous. This will cause a problem of overestimating indirect carbon emissions because the consumption of imported goods does not increase carbon emissions in China (Su & Ang, 2013). Third, we use consecutive data from 1995 to 2009 to demonstrate the increased rate of indirect household carbon emissions. Fourth, by combining regression analysis and scenario analysis, this study can predict the evolution of indirect household carbon emissions, which also overcomes the mentioned shortcomings of using IOA.

Meanwhile, one deficiency of WIOD data is the use of the current price value rather than the benchmark price in the input–output tables. Dietzenbacher and Temurshoev (2012) pointed out that the price indicator of the input–output table has little effect. Taking China's special pricing system and international exchange rate fluctuations into consideration, we use a gross domestic product (GDP) deflator to adjust the money terms in these IOTs. Therefore, the results presented in this paper are calculated by using comparable prices.

3. Methodology

3.1. Methods for calculating indirect carbon emissions from household consumption

Direct carbon emissions from household consumption are related to direct household energy requirements and the energy consumption mix. The direct carbon emission coefficient is calculated using carbon emissions and data from the WIOD's input–output tables of various sectors. For example, the CO_2 emission per unit of output of the i_{th} sector, which reflects the carbon emission intensity of this sector during production, is an important index of emission reduction. Assuming c_i^{pro} is the i_{th} sector's total carbon emissions from production, and x_i is the i_{th} sector's total output, the coefficient of direct carbon emissions can be calculated with Eq. (1).

$$c_i = c_i^{pro}/x_i\ ,\ \ i = 1, 2, ...,n \tag{1}$$

ICEH are calculated using the input–output model. We use the non-competitive input–output model to calculate indirect carbon emissions and use the input–output consumption expenditure in non-energy sectors to calculate indirect carbon emissions from household consumption. The vector T of ICEH can be calculated as follows:

$$T = C\widetilde{L}F^C \tag{2}$$

where C is a diagonal matrix of direct carbon emission coefficients, $\widetilde{L}$ is the Leontief inverse matrix, $\widetilde{L} = (I - A^D)^{-1}$ represents the total consumption relationship between products, which reflects production technology, and A^D is the direct domestic input coefficient matrix. Here, we should note that because the consumption of imported goods does not increase carbon emissions in China, we do not consider other countries' carbon emission in China's consumption. F^C is a column vector of the household consumption of non-energy products and

services.

3.2. Structural decomposition analysis of indirect household carbon emissions

The household consumption term in Eq. (2) is further decomposed into population size, consumption structure, and per capita consumption scale, as shown in Eq. (3).

$$F^C = P\hat{S}\bar{M} \tag{3}$$

where P is the annual population size, $\hat{S}$ is a diagonal matrix of the household consumption structure in non-energy sectors, and $\bar{M}$ is a column vector of the gross per capita household consumption in non-energy sectors.

Furthermore, population size can be further broken down into the reciprocal of the urbanization rate $1/r$ and urban population size u, and $P = (1/r)u$, as shown in Eq. (4).

$$\mathrm{T}= C\widetilde{L}(1/r)u\hat{S}\bar{M}\ . \tag{4}$$

By making substitutions from Eq. (2), we can obtain an elementary decomposition equation for the SDA model.

We set the benchmark time as 0 and the reporting time as 1. Then, we compare the T value of 0 time with that of 1 time.

When the number of determinants is n, the number of equivalent decomposition forms is $n!$ Dietzenbacher and Bart (2000) proposed a two-polar decomposition method, which is an algorithmic geometric average of all possible decomposition results. de Boer (2008) also pointed out that the average of any two symmetric decomposition forms can yield a good approximate estimating value. Therefore, this study uses the two-level decomposition method to decompose variable T. The two-polar decomposition way is shown in Eqs. (5) and (6).

$$\begin{aligned}\Delta T = {} & \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_0 = \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 - \\ & \hat{C}_0\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 + \hat{C}_0\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_1)u_1\hat{S}_1\bar{M}_1 + \\ & \hat{C}_0\widetilde{L}_0(1/r_1)u_1\hat{S}_1\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_0)u_1\hat{S}_1\bar{M}_1 + \hat{C}_0\widetilde{L}_0(1/r_0)u_1\hat{S}_1\bar{M}_1 - \\ & \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_1\bar{M}_1 + \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_1\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_1 + \\ & \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta T = {} & \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 - \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_0 = \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 - \\ & \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_0 + \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_0 - \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_0\bar{M}_0 + \\ & \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_0\bar{M}_0 - \hat{C}_1\widetilde{L}_1(1/r_1)u_0\hat{S}_0\bar{M}_0 + \hat{C}_1\widetilde{L}_1(1/r_1)u_0\hat{S}_0\bar{M}_0 - \\ & \hat{C}_1\widetilde{L}_1(1/r_0)u_0\hat{S}_0\bar{M}_0 + \hat{C}_1\widetilde{L}_1(1/r_0)u_0\hat{S}_0\bar{M}_0 - \hat{C}_1\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_0 + \\ & \hat{C}_1\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_0 - \hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\end{aligned} \tag{6}$$

The two-polar decomposition results are shown in Eq. (7).

$$\Delta T = g(\Delta\hat{C}) + g(\Delta\widetilde{L}) + g(\Delta r) + g(\Delta u) + g(\Delta\hat{S}) + g(\Delta\bar{M})\ , \tag{7}$$

where the direct carbon emissions coefficient effect is as follows:

$$g(\Delta\hat{C}) = \frac{1}{2}(\Delta C\widetilde{L}_1(1/r_1)u_1\hat{S}_1\bar{M}_1 + \Delta C\widetilde{L}_0(1/r_0)u_0\hat{S}_0\bar{M}_0)\ .$$

The technology effect is as follows:

$$g(\Delta\widetilde{L}) = \frac{1}{2}(\hat{C}_0\Delta\widetilde{L}(1/r_1)u_1\hat{S}_1\bar{M}_1 + \hat{C}_1\Delta\widetilde{L}(1/r_0)u_0\hat{S}_0\bar{M}_0)\ .$$

The urbanization rate effect is as follows:

$$g(\Delta r) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0\Delta(1/r)u_1\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1\Delta(1/r)u_0\hat{S}_0\bar{M}_0)\ .$$

The urban population effect is as follows:

$$g(\Delta u) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/r_0)\Delta u\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1(1/r_0)\Delta u\hat{S}_0\bar{M}_0)\ .$$

The consumption composition effect is as follows:

$$g(\Delta\hat{S}) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/r_0)u_0\Delta\hat{S}\bar{M}_1 + \hat{C}_1\widetilde{L}_1(1/r_1)u_1\Delta\hat{S}\bar{M}_0)\ .$$

The per capita consumption effect is as follows:

$$g(\Delta\bar{M}) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/r_0)u_0\hat{S}_0\Delta\bar{M} + \hat{C}_1\widetilde{L}_1(1/r_1)u_1\hat{S}_1\Delta\bar{M})\ .$$

Similarly, we decompose the variable of population size into three parts. First, it can be broken down into the reciprocal of the proportion of the population over 65 years old $1/o$, multiplied by the old-age population (over 65 years old) a. Second, we can also decompose the reciprocal of the population size into the proportion of the population 0–14 years old $1/e$, multiplied by the children-aged population (0–14 years old) b. Third, we decompose the population into the reciprocal of the proportion of the non-labor force $1/w$, multiplied by the non-labor population g $g = (a + b)$.

Therefore, Eq. (7) can be rewritten as follows:

$$\Delta T = g(\Delta\hat{C}) + g(\Delta\widetilde{L}) + g(\Delta o) + g(\Delta q) + g(\Delta\hat{S}) + g(\Delta\bar{M})\ , \tag{8}$$

where the proportion of the population over 65 years old for the population effect is as follows:

$$g(\Delta o) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0\Delta(1/o)a_1\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1\Delta(1/o)a_0\hat{S}_0\bar{M}_0)\ .$$

The effect of the population over 65 years old is as follows:

$$g(\Delta a) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/o_0)\Delta a\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1(1/o_1)\Delta a\hat{S}_0\bar{M}_0)\ .$$

Then, Eq. (7) can be rewritten as follows:

$$\Delta T = g(\Delta\hat{C}) + g(\Delta\widetilde{L}) + g(\Delta e) + g(\Delta b) + g(\Delta\hat{S}) + g(\Delta\bar{M})\ , \tag{9}$$

where the effect of the proportion of the population 0–14 years old is as follows:

$$g(\Delta e) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0\Delta(1/e)b_1\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1\Delta(1/e)b_0\hat{S}_0\bar{M}_0)\ .$$

The effect of the population 0–14 years old is as follows:

$$g(\Delta b) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/e_0)\Delta b\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1(1/e_1)\Delta b\hat{S}_0\bar{M}_0)\ .$$

Then, Eq. (7) can be rewritten as follows:

$$\Delta T = g(\Delta\hat{C}) + g(\Delta\widetilde{L}) + g(\Delta w) + g(\Delta g) + g(\Delta\hat{S}) + g(\Delta\bar{M})\ , \tag{10}$$

where the proportion of the population that is a non-labor force effect is as follows:

$$g(\Delta w) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0\Delta(1/w)g_1\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1\Delta(1/w)g_0\hat{S}_0\bar{M}_0)\ .$$

The non-labor force effect is as follows:

$$g(\Delta g) = \frac{1}{2}(\hat{C}_0\widetilde{L}_0(1/w_0)\Delta g\hat{S}_1\bar{M}_1 + \hat{C}_1\widetilde{L}_1(1/w_1)\Delta g\hat{S}_0\bar{M}_0)\ .$$

3.3. Multivariate regression analysis

A regression analysis provides the possibility of analyzing the relationship between background variables and the dependent variable of interest. When we divide the indirect household emissions into different determinants, we can also observe the relationships between six determinants. The findings indicate the important advantages of household consumption and one negative relationship between household consumption and urbanization. Therefore, we specify an econometric function for the relationship among the six determinants and suppose the coefficient of urbanization to be positive. In this part, the dependent variable T refers to the indirect carbon emissions from household consumption, C denotes the carbon emissions coefficient, and L

Table 2
Results of indirect carbon emissions regression.

Variables	Eq. α	Eq. β	Eq. χ	Eq. δ
Constant	−14564.08** (−3.24)	−18464.31*** (−4.96)	−8599.72** (−3.43)	−8700.08*** (−3.78)
C	575.31** (2.51)	765.57*** (3.84)	228.43* (2.28)	294.07** (2.71)
L	280.85* (2.36)	210.33** (2.39)	412.77** (3.20)	492.13*** (3.85)
P	0.116** (3.24)	0.149*** (5.25)	0.068** (2.93)	0.073*** (4.06)
r	−35.60* (−1.97)	−52.23*** (−3.68)	−31.25 (−1.36)	
S_ter			−1337.82* (−2.07)	−1799.78*** (−3.81)
S_sec	1873.85* (2.05)	2447.34** (2.90)		
o			218.52* (2.14)	
e	8.01 (1.09)			
M	45.92*** (6.38)	43.86*** (6.88)	28.12** (2.82)	36.51*** (5.65)
deflator	−210.63 (−1.19)		−302.29 (−1.94)	−432.40** (−2.74)
Adjusted R^2	0.986	0.986	0.989	0.986
AIC	7.953	8.006	7.720	8.046

represents technology. This model uses the maximum eigenvalue of the Leontief inverse matrix *L as* technology, the proportion of tertiary commodities consumption *S_ter*, and secondary commodities consumption *S_sec* as the consumption structure; *M* is the per capita household consumption in non-energy sectors, *P* is the variable of population size, *r* is the urbanization rate, *o* is the aging rate, *e* is the childhood rate, and *deflator* is the GDP deflator.

The regression results of the different combinations of the independent variables are shown in Table 2. Eq. β is a new equation of debugging after Eq. α, which removed the insignificant variables (*e* and *deflator*) from Eq. α. Similarly, Eq. δ removed the insignificant variables (*o*) from Eq. χ. In addition, the main difference between Eq. α and Eq. χ is the variable that contains a different consumption composition and demographic structures. Therefore, we use Eq. β as the prediction model and Eq. δ as the robustness test model because we find that the aging variable is not significant in Eq. α. We can see that six variables have passed the significance test, and these are the direct carbon emissions coefficient, technology, population, urbanization rate, consumption composition, and per capita household consumption in non-energy sectors.

In this study, we introduce the factors that can affect the indirect carbon emissions of residential consumption, which are decomposed in the structural decomposition model, and place them into the regression model, here using the stable characteristic of the regression model coefficients to predict the indirect carbon emissions of residential consumption. By continuously factoring the impact of decomposition into the model, this study summarizes two models that contain different independent variables. The first set of models, represented by Eq. α and Eq. β, is shown in Table 2. The factors included in Eq. α are the direct carbon emission coefficient, technology, population, urbanization rate, proportion of secondary industry, adolescent ratio, per capita consumption scale, and price. However, an explanatory variable in Eq. α is not statistically significant. By deleting the insignificant variables in Eq. α, we can obtain Eq. β, which we choose as the forecasting model. The second set of models, represented by Eq. χ and Eq. δ, is shown in Table 2. The difference between the two sets of models is that the proportion of the tertiary industry and the rate of aging in Eq. χ replace the ratio of secondary industries and the rate of adolescents in Eq. β. Similar to Eq. β, we can obtain the robustness testing model, shown in Eq. δ, by deleting the insignificant variables in Eq. χ.

ICEH are predicted by using the equation given in column (2) of Table 2. The equation is shown in Eq. (11).

$$\hat{T} = -18464 + 765.57C + 210.33L + 0.149P - 52.23r + 2447.34S\_\text{sec} + 43.86M, \quad (11)$$

where the variables *C*, *L*, *P*, *r*, *S_sec*, and *M* were estimated, as described in Fig. 2.

3.3.1. Direct carbon emissions coefficient (C)

We assume that in 2020 and 2030, China's carbon emissions per unit of output will also decrease by 40–45% and 60–65% compared with the values in 2005. High-, medium-, and low-intensity scenarios were simulated, and these are shown in Table 3. The high-intensity scenario reflects 45% and 65% reductions in carbon emissions in 2020 and 2030, respectively, compared with that in 2005. The medium-intensity scenario reflects 42.5% and 62.5% reductions, and the low-intensity scenario reflects 40% and 60% reductions. The annual reduction intensity targets in the periods 2009–2020 and 2020–2030 were interpolated based on average values.

3.3.2. Technology (L)

We select the largest eigenvalue of the Leontief inverse matrix as the technical variable (Chen & Yang, 2011). In this study, we use the rolling prediction method to predict the forecasting value of the technical variable in the period 2010–2030. Rolling prediction is also known as continuous prediction, which is a constant stability forecasting method used to maintain a certain forecast period (such as five years). It is worth mentioning that the sixth forecasting values are predicted based on the five previous consecutive years (e.g., we will predict the technology value of 2016 based on the data in 2011–2015 and then predict the value of 2017 based on the data in 2012–2016); therefore, the forecasting period can be maintained for five years as a benchmark.

3.3.3. Population (P)

Considering the influences of China's population policies is necessary to predict the population growth rate. This study uses the results of Chen, Dietzenbacher, and Los (2017), who reported reasonable predictions of the population trends in China by using a constant fertility rate scenario and a two-child policy scenario.

3.3.4. Urbanization rate (r)

We use actual data to supply the urbanization rate from 2010 to 2016 and then to predict the urbanization rate with the rolling prediction method from 2017 to 2030. The forecasting value of the urbanization rate is around 62% in 2020 and 70% in 2030.

3.3.5. Consumption per capita (M) and consumption composition (S_sec)

In 2009, the household consumption in China reached 16,635 million yuan, which is 5.49 times the amount in 1995. A regression analysis is used to predict future consumption per capita (binomial fit; $R^2 = 0.96$). In 2020 and 2030, the consumption scaled per capita will be US$3587.50 and US$7069.65, respectively. We assume that the growth ratios of secondary industry structures are −1.24%, −0.74%,

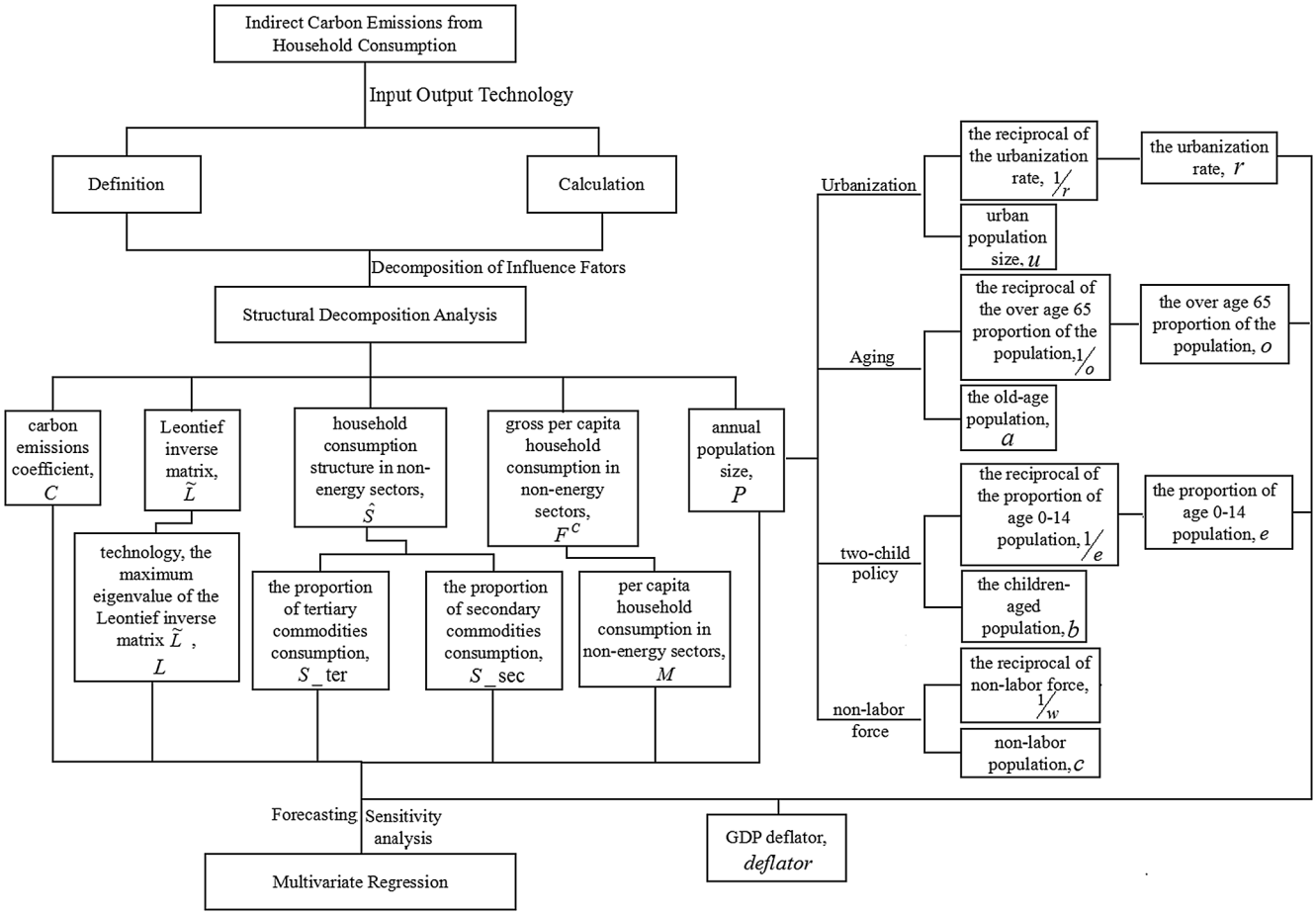
Indirect Carbon Emissions from Household Consumption
Input Output Technology
Definition
Calculation
Decomposition of Influence Fators
Structural Decomposition Analysis
carbon emissions coefficient, C
Leontief inverse matrix, $\tilde{L}$
household consumption structure in non-energy sectors, $\hat{S}$
gross per capita household consumption in non-energy sectors, F^c
annual population size, P
technology, the maximum eigenvalue of the Leontief inverse matrix $\tilde{L}$, L
the proportion of tertiary commodities consumption, S_ter
the proportion of secondary commodities consumption, S_sec
per capita household consumption in non-energy sectors, M
Urbanization
the reciprocal of the urbanization rate, 1/r
the urbanization rate, r
urban population size, u
Aging
the reciprocal of the over age 65 proportion of the population, 1/o
the over age 65 proportion of the population, o
the old-age population, a
two-child policy
the reciprocal of the proportion of age 0-14 population, 1/e
the proportion of age 0-14 population, e
the children-aged population, b
non-labor force
the reciprocal of non-labor force, 1/w
non-labor population, c
Forecasting
Sensitivity analysis
Multivariate Regression
GDP deflator, deflator

Fig. 2. The definition of variables and model description.

Table 3
Total CO_2 emissions from household consumption in 1995–2009 (Million tons).

	ICEH (1)	DCEH (2)	TCEH (3) = (1) + (2)	CEP (4)	TCE (5) = (2) + (4)	Share in TCEH (6) = (1)/(3)	Share in TCE (7) = (1)/(5)
1995	720	351	1072	2723	3074	67%	23%
1996	764	360	1125	2797	3157	68%	24%
1997	748	331	1079	2762	3093	69%	24%
1998	820	279	1099	2928	3207	75%	26%
1999	811	282	1092	2817	3099	74%	26%
2000	803	296	1099	2805	3101	73%	26%
2001	801	299	1101	2851	3150	73%	25%
2002	811	306	1117	3072	3377	73%	24%
2003	822	330	1151	3564	3894	71%	21%
2004	841	368	1209	4255	4623	70%	18%
2005	849	397	1245	4686	5083	68%	17%
2006	874	417	1291	5108	5525	68%	16%
2007	939	440	1379	5522	5963	68%	16%
2008	1008	475	1482	5923	6398	68%	16%
2009	1080	482	1562	6214	6696	69%	16%

Notes: ICEH = indirect carbon emissions from household consumption; DCEH = direct carbon emissions from household consumption, or carbon emissions in household; TCEH = total carbon emissions from household consumption; CEP = carbon emissions in production; TCE = total carbon emissions.

and −0.24% (average growth ratio in 2010–2020), as well as −0.63%, −0.13%, and 0.37% (average growth ratio in 2021–2030), at the high-, medium-, and low-speed scenarios, respectively. Therefore, the results of the secondary industry structures in the three scenarios are 29%, 31%, and 32% in 2020 and 27%, 30%, and 34% in 2030.

4. Results and analysis

4.1. Data source

The data utilized in this article are the latest published Chinese input–output tables and sectoral carbon emissions data from WIOD from 1995 to 2009 (Dietzenbacher, Bart, Robert, & Marcel, 2013; Sebastian, Enrica, Michael, & Elena, 2014; Valeria & Stefano, 2016). WIOD data have the following advantages: (1) WIOD provides a non-competitive input–output table that distinguishes the difference between domestic and imported goods; (2) the data are consecutive, which means there is a certain level of convenience in comparatively analyzing a time series; (3) the tables for each year have the same structure, and sectors are uniform, which is beneficial for a comparative analysis among sectors and for the prediction of the trend of residential indirect carbon emissions; and (4) carbon emissions data are also available and calculable from the WIOD database, ensuring the accuracy and consistency of the research results. However, one deficiency of WIOD data is that the input–output tables use the current price value rather than the benchmark price. Dietzenbacher and Temurshoev (2012) found that all predicted effects were very similar when considering the effect of an exogenous stimulus of final demand in current prices on the gross output in constant prices. Considering China's special pricing system and international exchange rate fluctuations, we use a GDP deflator to adjust price in terms of these IOTs. Therefore, the results presented in this paper are calculated using comparable prices.

4.2. Indirect carbon emissions from China's household consumption

With Eq. (2), the annual ICEH changed from 720.44 million tons in

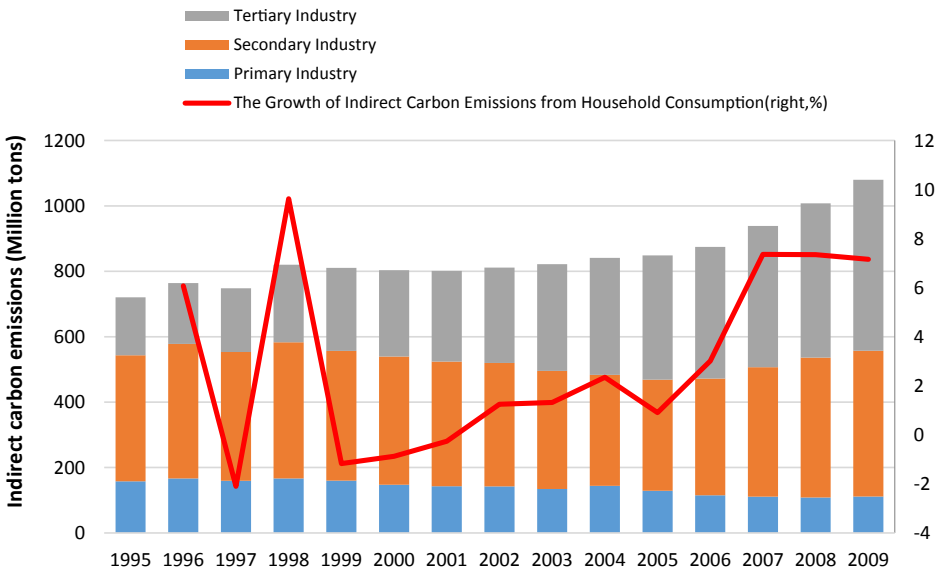

Fig. 3. Indirect carbon emissions from household consumption by industries.

1995 to 1080 million tons in 2009. In Table 3, we can see that a share of 67–75% of residential carbon emissions comes from indirect carbon emissions, which is kept at a reasonably stable level because of the increasing ICEH. In this study, the total carbon emissions from households equal the direct carbon emissions from household consumption in energy commodities plus indirect carbon emissions from non-energy household consumption. From the perspective of production, total carbon emissions can be calculated using carbon emissions in production plus household carbon emissions. Based on an estimation of carbon emissions in production, the indirect carbon emissions from households are a part of the final demands of household consumption. Compared with carbon emissions from production, ICEH contributed to only 16–26% of total carbon emissions, and their rate of contribution has decreased significantly since 2003.

Fig. 3 shows the ICEH in three industries in 1995–2009. In the period 1995–2006, the ICEH were kept at a reasonably stable increasing trend, but they began to grow rapidly between 2006 and 2009. In 2009, the contribution of primary industry product consumption to the total indirect household carbon emissions dropped from 22% in 1995 to 10% in 2009. Indirect carbon emissions from the consumption of tertiary industry products have become the primary source of indirect household carbon emissions and comprised approximately 50% of the ICEH, increasing from 25% in 1995 to 48% in 2009. The indirect carbon emissions from secondary industry consumption decreased from 54% in 1995 to 40% in 2009. Since 1998, the ICEH from tertiary industry consumption have significantly increased from 237 to 523 million tons. The growth rate of ICEH from tertiary industry consumption was markedly faster than that from the secondary industry because of the rapidly increasing consumption expenditure of the health and social work sector, the education sector, other communities, and the social and personal services sector.

Table 4 shows that the ICEH from tertiary industry consumption were markedly higher than those from the secondary industry because of rapidly increasing consumption expenditures in the health and social work sector, the education sector, other communities, the social and personal services sector, the hotels and restaurants sector, and wholesale trade and commission trade, save for the motor vehicles and motorcycles sector. The large ICEH are also closely related to secondary commodities, which are dominated by the food, beverages and tobacco sector, textiles and textile products sector, electrical and optical equipment sector, and transport equipment sector. ICEH come mainly from the use of food, health, and education to meet the needs of household consumption.

4.3. Structure decomposition analysis

From 1995 to 2009, numerous factors, such as urbanization, household consumption per capita, the change in consumption behavior, and the carbon emission coefficient, have contributed to an increase in ICEH. Therefore, we analyze the change in indirect carbon emissions based on Eq. (7). Fig. 4 illustrates the impact of various factors on indirect carbon emissions. From the overall results, the carbon emissions coefficient and household consumption per capita are the main determinants for the ICEH change in 1995–2009 because the negative effect of the decreased carbon emissions coefficient generally offsets the positive effect of the increased consumption scale.

The features of the indirect emissions of household consumption are shown below.

4.3.1. Feature 1: Consumption-oriented emission is a major characteristic

Fig. 2 shows that the decomposition of household consumption is divided into five factors, of which the per capita consumption scale is the largest positive factor, leading to an increase in the indirect emissions of household consumption. From 1995 to 2009, the average annual growth rate of the average per capita consumption in China was as high as 8.8% (excluding the price factor from the GDP deflator). The per capita consumption in 2009 was 3.26 times that in 1995. The rapid increase in per capita consumption makes the per capita consumption scale the most important driving factor for the growth of indirect carbon emissions in China. However, compared with that of developed countries, China's per capita consumption scale is still relatively low and has great potential for development. Therefore, in the integrated effect of population growth and consumption composition upgrading, the per capita consumption scale effect of household indirect carbon emissions in China will have a positive impact over a long period of time. This trend will result in an increase in the indirect emissions of household consumption.

We can see some specific results for different industries. As the share of household consumption decreases in products produced by a certain industry, such as agriculture, food and beverage, tobacco manufacturing, chemical, and other non-metallic mineral products, the proportion of carbon emissions caused by the production of these

Table 4
The Top 8 categories share of ICEH in 1995–2009.

	Food	Health	Agriculture	Education	Textiles	Other Services	Hotels	Wholesale	Total
1995	21%	3%	22%	2%	5%	2%	3%	4%	62%
1996	21%	3%	22%	2%	5%	2%	3%	4%	63%
1997	21%	4%	21%	2%	5%	2%	3%	4%	63%
1998	20%	4%	20%	3%	6%	3%	4%	4%	64%
1999	18%	4%	20%	4%	6%	4%	4%	4%	64%
2000	17%	4%	18%	4%	6%	4%	5%	4%	62%
2001	16%	3%	18%	4%	6%	5%	5%	4%	62%
2002	16%	3%	18%	5%	7%	5%	6%	4%	63%
2003	16%	5%	16%	5%	6%	5%	6%	5%	65%
2004	16%	6%	17%	6%	6%	6%	7%	5%	68%
2005	18%	8%	15%	6%	6%	6%	7%	3%	68%
2006	19%	9%	13%	7%	6%	6%	7%	3%	70%
2007	19%	9%	12%	6%	6%	6%	6%	5%	70%
2008	19%	10%	11%	6%	6%	6%	6%	6%	71%
2009	18%	11%	10%	7%	6%	6%	6%	6%	71%

Notes: Food = Food, Beverages and Tobacco; Health = Health and Social Work; Agriculture = Agriculture, Hunting, Forestry and Fishing; Education = Education; Textiles = Textiles and Textile Products; Other services = Other Community, Social and Personal Services; Hotels = Hotels and Restaurants; Wholesale = Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles.

consumer products to the indirect emissions of household consumption declines. On the contrary, with an increase in household consumption share in the industry, such as with electricity thermodynamic water production and supply, accommodation and catering, education, health, and social services, and other community services, the resulting indirect emissions of household consumption rise year by year. This shows that in the future, China will still be oriented toward having consumption emissions. Therefore, the transformation and upgrading of the household consumption structure will become an important driving force for future emission reductions. Only by accelerating the optimization and upgrading of the consumption structure can we fundamentally change the situation of high consumption, which is caused by the high emissions, and can then effectively alleviate the paradox of economic growth and energy security.

4.3.2. *Feature 2: The effect of population size is gradually diminishing*

The decomposition results in 1995–2009 show that the effect of population size on the indirect emissions of household consumption has gradually weakened. However, with the liberalization of the two-child policy, population growth will continue in the future. The high birth and aging rates will increase the uncertainty of households' energy consumption and indirect emissions.

Although the population effect is not less important than the other determinants, the population markedly affects ICEH because the total household consumption still plays a dominant role in increasing ICEH. In 1995–1996, the expansion of the population made carbon emissions increase to 9 million tons, representing a 17% contribution rate. A further decomposition analysis shows that the urbanization rate, the aged population, and the labor force have significant effects on the

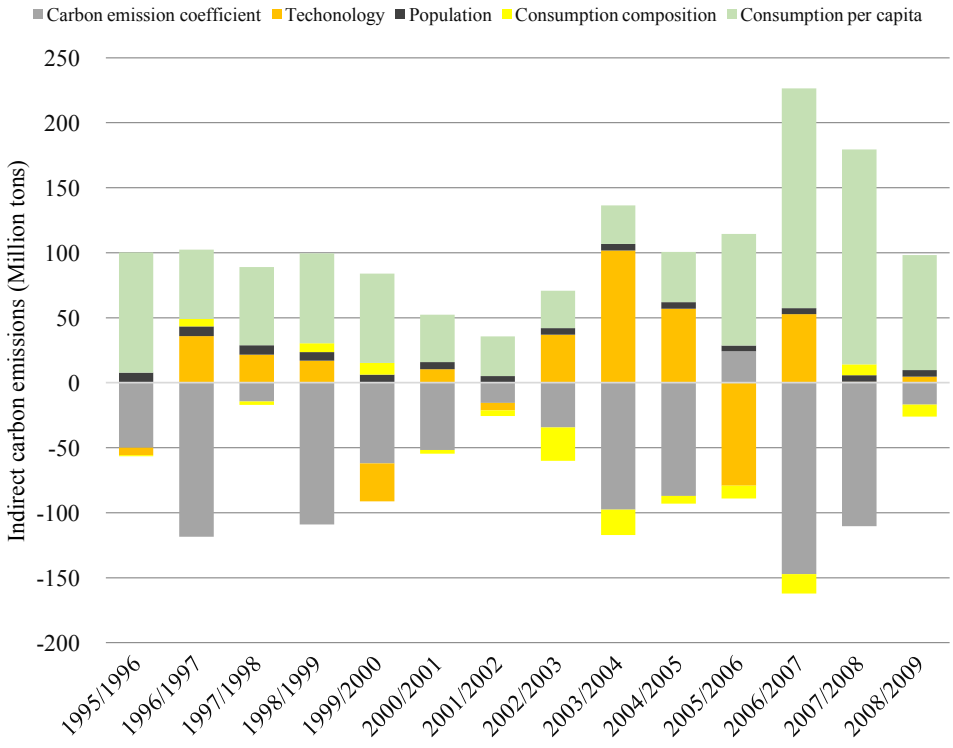

Fig. 4. The impact of different factors on indirect carbon emissions.

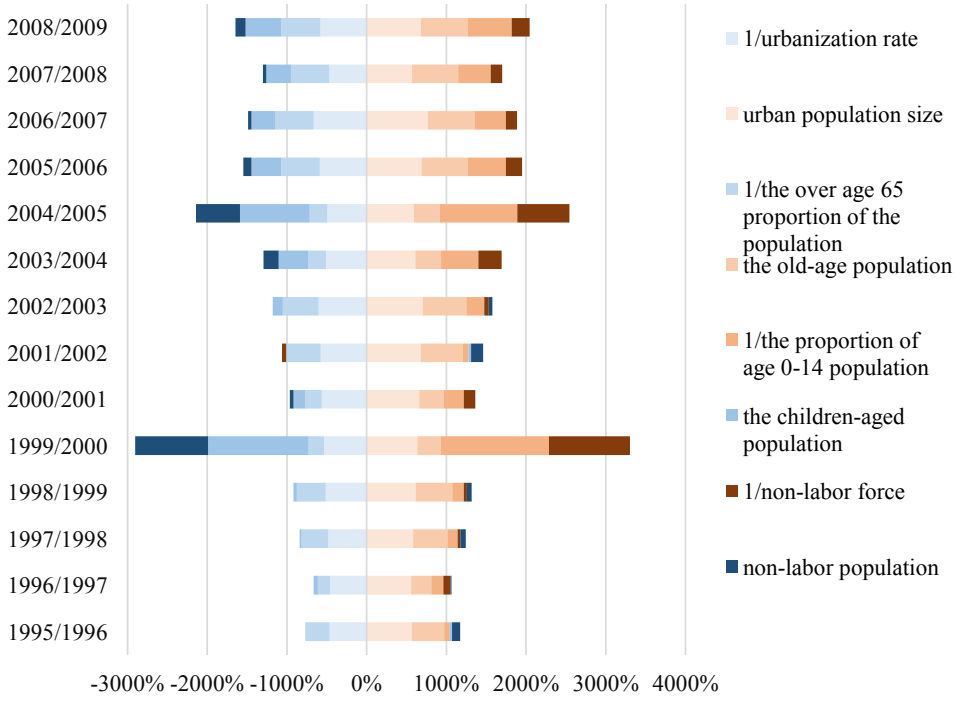

Fig. 5. The impacts of population on indirect carbon emissions.

ICEH. Fig. 5 shows that the reciprocal of the proportion of the population aged 0–14 years, the non-labor force, and urbanization have a positive effect. This means that aging and urbanization are effective in reducing the ICEH. Meanwhile, these factors were more significant in 1999–2000, 2004–2005, and 2008–2009 than in other years.

4.3.3. Feature 3: Energy-saving technological advances play an important role.

Fig. 4 shows that the technical effect consists of two factors: energy-saving technological advances and generalized technological advances; for these factors, the former is represented by the direct carbon emission coefficient, which can reflect the efficiency of energy use, and the latter is represented by a Leontief inverse matrix, which can reflect a generalized technological progress for the level of production technology. On the one hand, reducing the direct carbon emission coefficient has a negative effect on the indirect carbon emissions generated by the production of consumer goods, which has significantly reduced the indirect emissions of household consumption. Specifically, the indirect carbon emissions of household consumption in industries, such as agriculture, food and beverage, tobacco manufacturing, textile, chemical, accommodation, and catering, have been decreasing year by year under the influence of direct carbon emission reduction. For example, the energy saving technology of the agriculture sector and the food and beverage and tobacco manufacturing industries has achieved good reduction effect. The direct carbon emission coefficient of the agriculture sector was reduced from 0.44 tons/US dollar in 1995 to 0.21 tons/US dollars in 2009, whereas the value was decreased from 0.65 tons/US dollars in 1995 to 0.14 tons/thousand US dollars in 2009 in the food and beverage and tobacco manufacturing industries. This shows that from 1995 to 2009, energy-saving technological advances have played a major role in household emission reductions in China. The direct carbon emission coefficient is the most crucial factor for promoting the decrease in indirect emissions of household consumption in China.

On the other hand, the generalized technological effect is the main factor leading to the increase in indirect emissions of household consumption. In most years, it has been positively influenced by indirect emissions reduction, indicating that the level of management, economies of scale, and industrial layout needs to be urgently improved. Changes in the level of production technology in industries, such as agriculture, food and beverage, tobacco manufacturing, and chemical, have led to an increase in indirect carbon emissions from household consumption. For energy-intensive industries, such as paper making and printing, electro-optical equipment manufacturing, and the supply and production of electricity and thermodynamic water, changes in the level of production technology in most years have played a positive role in emission reduction. The generalized technological effect showed a negative impact in both 1999–2000 and 2005–2006. This result shows that generalized technological advances contribute to the reduced emissions in the two periods, and these are conducive to reducing the indirect emissions of household consumption, as well.

4.3.4. Feature four: The potential for emission reductions in the effect of consumption structure is large

The effect of the consumption structure shows obvious differences in two phases: before and after 2000. Before 2000, the effect of the consumption structure was basically positive. The change in consumption structure promoted the increase of indirect carbon emissions. However, since 2000, the effect of consumption structure has been negative for most years, and its absolute value has increased. This shows that the change in consumption structure has led to a significant reduction in indirect carbon emissions and a further reduction in indirect carbon emissions from household consumption. At the industrial level, the effect of the consumption structure also shows different effects among the three major industries. The increase in consumption demand for the tertiary industry's products has led to an increase in the carbon emission of the tertiary industry as a result of the effect of the consumption structure, whereas the carbon emission of the first and second industries has decreased. This also reflects the development of China's household consumption structure. In 1995, the structure of the three major industrial products consumed by residents in China was 31.09%, 40.33%, and 28.58%, whereas the structural adjustment was changed into 12.78%, 33.26%, and 53.96%, respectively, in 2009. The proportion of the tertiary industry's products has risen sharply and became the main force behind household consumption.

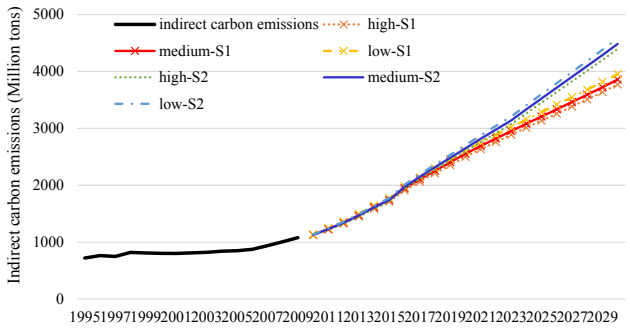

Fig. 6. Trend of indirect carbon emissions from China's household consumption.

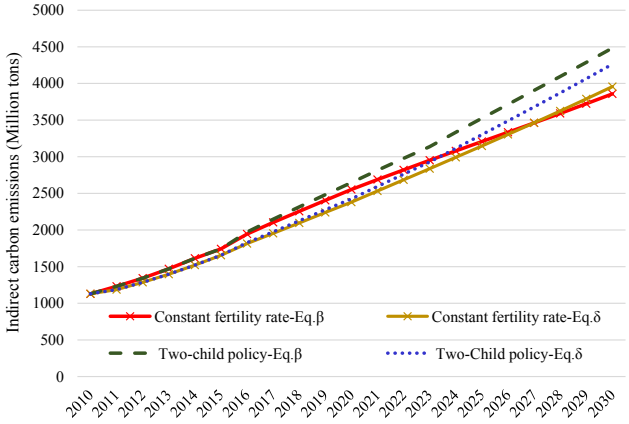

Fig. 7. Sensitivity analysis.

4.4. Multivariable regression analysis

The SDA model regards the direct carbon emissions coefficient (C), technology (L), population (P), urbanization rate (r), consumption per capita (M), and consumption composition (S) as the independent variables for ICEH, which is given by Eq. (7). A 1% change in these determinants (or variables) would bring less than (or more than) 1% change in the ICEH. After a regressions model is used, the relationship between the SDA model and regression model can be seen, as presented in Eq. (11). The independent variables P are decomposed in this study to further understand the influence of other determinants on the ICEH.

The large ICEH have a close relationship with household consumption, which is dominated by population growth and consumption composition. Meanwhile, the consumption expenditure will expand further, which also causes an increase in carbon emissions. It is a paradox that China's government not only guides the low carbon pathway of household consumption but also stimulates the economy by expanding domestic demands. Based on all scenarios, changes in population growth are the leading determinants of indirect carbon emissions from household consumption.

In Fig. 6, we assume two scenarios of population development: S1 is a constant fertility rate scenario, and S2 is a two-child policy scenario. In the two scenarios, the ICEH show an increasing trend; however, both growth rates are lower than those in previous years. Each scenario has three levels: low, medium, and high. Because of the low proportion of tertiary industry consumption and the low levels of carbon intensity reduction, the largest amount of household carbon emissions and the highest growth are observed in the low S2 scenario. However, in the high S1 scenario, the results are reversed. In the medium-level situation, the average population growth rate is 4.54% in S1 and 5.16% in S2. For the forecasting value of the ICEH, compared with 2008, there is a 78.61% increase to 2337 million tons in 2020 in S1 and an 83.43% increase to 2401 million tons in S2. As for the results in 2030, compared with the previous decade, the growth rate has decreased significantly to 41.87% and 55.57% in S1 and S2, respectively. The forecasting value of household carbon emissions is up to 3316 million tons in S1 and 3735 million tons in S2.

4.5. Sensitivity analysis

Whenever a theoretical input–output framework is developed, the most important consideration is validating it. This study reports the results from the SDA and regression model and uses sensitivity analysis to check and prove the model we developed.

A further sensitivity analysis shows that the proportion of secondary commodities in total consumption S_sec drove the change in indirect carbon emissions, which is illustrated in Fig. 3. We chose Eq. δ as the robustness test, where the consumption composition of the tertiary industry products S_ter was used instead of the determinant S_sec. At the same time, we also added the determinant *deflator* into the sensitivity analysis.

In Fig. 7, the solid and dotted lines indicate the household carbon emissions in S1 and S2, respectively, which show that household carbon emissions are higher in the S2 scenario. However, the difference in household carbon emissions between the two scenarios decreases if we change the tertiary industry's portion to the secondary industry, especially in 2030. Specifically, it demonstrates that the model is fitting and stable for this case.

Through robustness testing, we can see that the impact of the proportion of consuming tertiary products S_ter on the indirect carbon emissions of resident consumption is negative. A 1% increase in proportion of the consumption of tertiary products can create 1799.78 million tons of carbon emissions in indirect emissions of household consumption. In addition, the regression coefficient of population factor P in the robustness testing model Eq. δ is lower, which makes the difference in the changes of indirect emissions of household consumption under the two population scenarios less than that of the forecasting model Eq. β. As shown in Fig. 5, the predicted value of the robustness testing for Eq. δ in S1 (constant fertility rate) differs from the predicted value for Eq. β by an average of 3.5%. In S2 (two-child policy), there is a difference of 6.0%, indicating that the robustness of the analysis results is better, and there is no large prediction error because of the change of variables. Second, in the robustness testing for Eq. δ, the differences of the indirect carbon emission path of household consumption reflected in S1 and S2 are smaller. In S2, indirect carbon emissions are only 1.04 times that of S1, and the maximum difference is 7.7%. However, in the forecasting model, Eq. β, the difference between the two scenarios is 1.08 times, and the maximum difference is 16.2%.

5. Conclusions and policy implications

Population growth and rapid urbanization are not only increasing the demand for housing units but are also are increasing indirect carbon emissions. However, at the moment, a standardized tool for predicting indirect carbon emissions for typical housing units based on decomposition analysis results is unavailable. The current study aimed to develop a framework for determining, predicting, and assessing the respective indirect effects of carbon emissions on population, energy, and economic policies. A new approach that combines the multivariable regressions analysis technique with input–output technology and structure decomposition analysis (SDA) was developed to account for the driving forces of ICEH and help improve the prediction of ICEH. There are many determinants of ICEH, such as the direct carbon emissions coefficient, the number of households, or the average size of households. In this study, we decomposed ICEH into five factors based on an input–output table and the SDA model regarding the direct carbon emissions coefficient, technology, population, urbanization rate, consumption per capita, and consumption composition as independent

variables for ICEH. The conclusions and policy implications are as follows:

First, urban employment, disposable income, and tertiary industries have different effects on the ICEH across countries and cities. For urban employment, rapid urbanization and the two-child policy are the main reasons why the population variable has a positive effect on increasing the ICEH. The projection is that by 2050, the total urban population will reach 66% of the global population, leading to a greater energy demand. In addition, the increasing household incomes and improved living standards will bring a serious threat to climate change responses. China's population growth will cause an increase in residential carbon emissions. Therefore, anticipating the increasing trend of China's demographics with the two-child policy and maintaining a reasonable population growth are particularly important to slow down the increasing trend of residential carbon emissions by adjusting other driving factors. Our prediction results show the ICEH growth rate will slow down under the two-child policy because of an adjustment of other determinants, such as consumption composition and technical progress in energy-intensive sectors.

Second, we found that the variation trend of consumption composition is positively correlated with ICEH. The development of tertiary industries relies on secondary industries and demographic consumption characteristics, such as the two-child policy and carbon-intensive consumption patterns. Tertiary industries can increase ICEH when they depend on an increase in recreation consumption and medical and health consumption. Our results show that the steady and continuous increase in ICEH is mainly trouble lines because of the stable consumption of secondary industry products and the rapid growth of consumption of tertiary industry products.

As evident in the above, there are several policy implications for the government and other decision-making organizations. From the aspect of population uncertainty, we suggest that a combination of policies pointing to the two-child policy should be promulgated to balance the increase in population and total consumption. The government should promote the low carbonization of lifestyle and green consumption patterns while putting forward the population policy. From a technology aspect, the development of various industries in China remains unbalanced, and industries' internal development is uncoordinated, leading to an increase in indirect emissions of household consumption. We propose that the government should continue to promote energy-saving technological advances and optimize the industrial structure in order to save energy and reduce emissions. From the aspect of a low-carbon consumption behavior, we suggest that policy makers should focus on changing residents' consumption behavior and optimizing consumption composition. Both approaches would make a considerable contribution toward achieving a reasonable low-carbon pathway, where households would consume more low-carbon products and cleaner energy while still enjoying a comfortable and high quality of life.

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